Establish Control Algorithm By Using Machine Learning In Thermal Comfort Prediction To Maximize User Comfort and Reduce Electricity Consumption

by

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1 Abstract

Machine learning has discovered many decades ago, but it was limited by the computational power of a machine at that time. However, more and more advanced technologies are discovered, the limitation of machine learning is almost diminished. By taking advantage of the power of machine learning, this project aims to use the deep neural network (DNN) to classify the user's thermal comfort levels and develop a control algorithm for maximizing the user's satisfactory and minimizing the power consumption of the air conditioner. By using different sensors to collect the environment data and the user's skin temperature, the DNN could classify the 7 thermal comfort levels (very cold, cold, a bit cold, comfy, a bit hot, hot, very hot) with an accuracy at about 60% using only 20 hours training time.

2 Acknowledgement

I would like to express my deep gratitude to Professor Chen Chun, my final year project supervisor, for his supports and encouragement. With his motivation, I am able to propose my own topic and explore my future path on engineering.

Special thanks should be given to Mr. Check Chi Ming for providing many technical advices on electronics throughout the project.

3 Table of Contents

3.1 Background knowledge and literature review

The thermal comfort prediction involves the physics model behind the environment and the human thermoception. The human thermoception affects by the thermoreceptors. There are two thermoreceptors, which are cold and warm receptors. [1] The skin temperature is normally at 30°C to 36°C, which no thermal sensation is noted. [1] However, the relative distribution of the thermoreceptors of the hand did not have much studies at 2006, so it was not known to different regions of the hand could reflect the thermal sensation. [1]

The neural network will be used in this project. It is a tool that perform regression or classification by using different combination of neurons and layers. In this project, the neural network will be supervised learning. It means that the data we collected is labelled with corresponding type. For simple classification problem, we suggest a hypothesis function h to make prediction of input data x, such that the h(x) could predict the correct classes. [2] And for neural network, it expands the hypothesis function to different hypothesis function with different weight. Every neuron inside the neural network could have different weights correspond to the input data x. And the layers contain the multiple neurons and each neuron inside the layers will connect to the next layer neurons, until it reaches to the output layer, and the process is called forward propagation. [2]

In order to update the weights inside the neurons, a backward propagation is used. But before backward propagation, gradients is needed to calculate in order to let the hypothesis function reach to the global optimal points. There are different methods to calculate the loss of the function. For classification, there are Binary Cross-Entropy Loss, Categorical Cross-Entropy and Sparse Categorical Cross-Entropy. [2] The loss is used to find the difference between the correct output data and the predict output data. After finding the loss, optimizers are used to perform the update, such as Stochastic Gradient Descent, RMSprop and Adam. [2] Difference optimizers perform slightly different and with different settings. After the running through multiple training epochs, the hypothesis function will have the updated weights which will have much higher accuracy than the original one, presume the data has high correlation between each other.

4 Problem description

Hong Kong has a sub-tropical climate, where the average humidity from January to November is above 70%. The humid air throughout the year contributes a great impact on indoor thermal comfort. For most of the residential household in Hong Kong, they install air conditioner units at multiple rooms in their apartment. For most traditional air conditioners, the user needs to control the temperature and the fan speed manually according to their experience on the performance of the air conditioner and their thermal comfort zone.

However, the control tactics of the air conditioner are a complex function, and the cooling results may vary due to different factors, like humidity and user's metabolic rate. For example, if the user feels hot, he may set the temperature of the air conditioner to a low level, which is much lower than his actual needs. This control tactic may fulfil his cooling requirement, but it may cause another problem which is over-cooling. The room temperature drops rapidly to a level that is more than enough to cool down the user, thus, it may lead to waste of energy and discomfort of the user.

As a result, good control tactics for manipulating the air conditioner settings needs to fulfill two conditions. The first is the action it takes needs to maximize the user thermal comfort. The second is the action it takes needs to minimize the waste of energy. Under the two conditions, the control tactics require to be predictive to the different possible outcomes after taking an action. This type of optimization problem is complex, as it considers not only the power consumption but also the user's thermal comfort zone. Human thermal comfort zone varies with numerous factors, such as the metabolic rates, the clothing level, the indoor temperature, and the humidity.

Due to the progressively discoveries on Artificial Intelligence, complex problems are possible to find a solution and analyze. It is especially strong at solving real-life problems, such as autonomous vehicle, speech recognition and face recognition. Smart appliances on controlling the air conditioner are one of the products that take advantage on using Artificial Intelligence. Most of them analyze the user's preferences and predict the user future selection on different things, thus, it tends to maximize the user convenience. However, the smart appliances are not popular in Hong Kong due to two reasons. Firstly, the price is not affordable when comparing to other traditional appliances. Secondly, the users tend to replace their appliances when they are broken. Therefore, to satisfy the requirements, the smart appliance needs to be low budget, and it is not targeting to replace the original appliances.

Therefore, designing a device to transform a traditional air conditioner to a smart air conditioner could save a lot of money comparing buying a new one. There are three main problems in designing this device. Firstly, it should provide good control tactics on manipulating the air conditioner by learning the user's thermal comfort zone and the air conditioner cooling algorithm. Secondly, the device should provide a platform for user give feedback about his current comfort and current status of the air conditioner. Thirdly, it requires multiple hardware and software components to gather indoor environment data and user data and to input to the control algorithm.

5 Proposed solution methods

5.1 Overview

To transform a traditional air conditioner to a smart air conditioner, the traditional remote will be replaced by a smart remote. The new remote provides automatic temperature setting according to your thermal comfort and the environment data. It collects the environment data, such as indoor temperature and indoor humidity, and it sends the data to online server for analyzing.

Besides, a device and a platform are needed to collect the user status. To analyze the user's thermal comfort zone, it needs to collect both direct and indirect feedback. For direct feedback, it is the user's input about his feeling about the indoor environment, such as cold or hot. By using a mobile application, the user can send his feedback whenever he needs, and he can also monitor the indoor environment and the current setting from the control algorithm. For indirect feedback, it is by measuring the user's skin temperature to analyze his thermal comfort zones. By using a device to wrap on his wrist, it could record the change his skin temperature and send the data to online server for analyzing.

5.2 Tasks

5.2.1 Software Development

The software development part involves three sections. The main section was the thermal comfort prediction, which acted as the base of the air conditioner control algorithm. The other two section were the online database server and the mobile application. These two sections increased the feasibility of the control algorithm to be applicable on real-life situations.

5.2.1.1 Thermal Comfort Prediction

By using a supervised learning model, the deep neural network (DNN) will attempt to classify the user's thermal comfort. The model analyses the relationship between different input features and different thermal comfort results. Thus, it sorts out the most reliable air conditioner (AC) setting which will receive a user's satisfactory.

In the DNN, there are 7 inputs data which are the indoor temperature, the indoor humidity, the outdoor temperature, the outdoor humidity, the user's skin temperature, the set-temperature and the set-fan-speed. The output data are 7 thermal comfort levels that are predefined to indicate how the user feels in a specific state. It includes "very hot", "hot", "a bit hot", "comfy", "a bit cold", "cold" and "very cold". There are two reasons why dividing into three main classes, which are hot, cold and comfy, instead of comfort and discomfort. Firstly, comfy data separate hot data and cold data, and the function for clustering the two sections is more complex than the three sections. Secondly, the information that could get from more levels contributes more to understanding the factors that are affecting the specific type of thermal sensation.

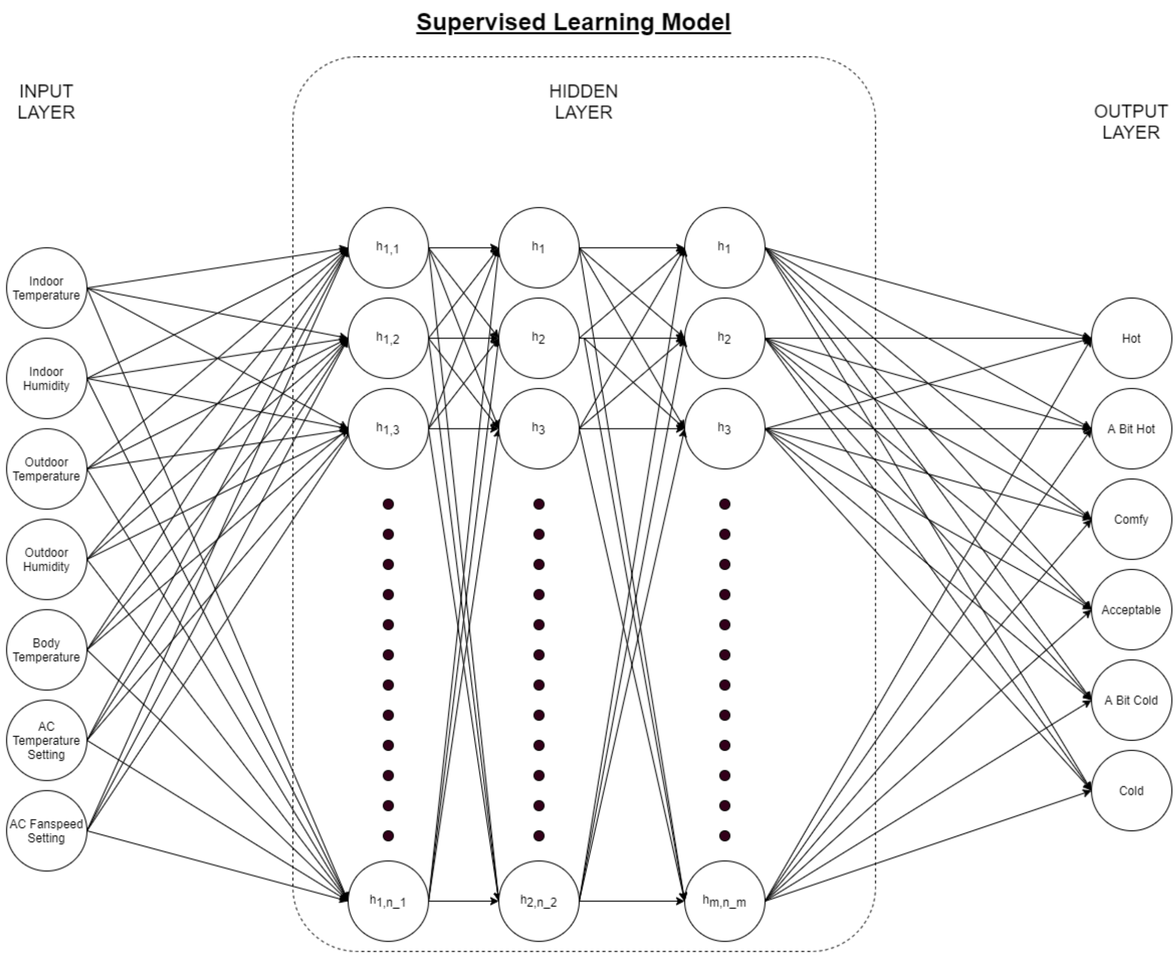

Figure 5-a structure of the DNN

In order to estimate the probability of get a thermal comfort levels, a softmax function is added at the output layer. It output a matrix with a size 1x7, and it contains the probability distributions of the thermal comfort levels. The highest probability in the output matrix implies that the current situation will mostly get this thermal comfort level. As the set-temperature and the set-fan-speed are the inputs of the DNN, by inputting the other features with all the control actions, which are the combinations of the set-temperature and set-fan-speed, it predict and sort out actions that will return a highest probability of receive a “comfy” feedback.

As the DNN was solving a classification problem, and there were multiple classes for the output. The Categorical Cross-Entropy was chosen to be the loss function. [3] The DNN was a sequential model, and it consisted with 3 hidden layers, which have 128 neurons, 512 neurons and 128 neurons accordingly. The activation applied on each layer was leaky ReLU function. The leaky ReLU function conserves more data when x < 0 comparing to normal ReLU function, which could prevent losing gradients when using it.

$$Leaky\ ReLU,\ \ f(x) = \begin{cases} x & if\ x > 0 \\ 0.01x & otherwise \end{cases}$$

$$ReLU,\ \ f(x) = \begin{cases} x & if\ x > 0 \\ 0 & otherwise \end{cases}$$

5.2.1.2 Online Database Server

The online database server acted as a central platform for all the other devices and programs to access all the sensors data, feedback from user, control actions from the algorithm and user personal data. It provided a real-time update function, so the newest sensors data could be used to estimate the control action without delaying. It also sorted out different users' devices to prevent wrong device connection and control action. Google Firebase could be used for hosting the online database server. The database server needed to be designed to fulfill multiple users' situations. Therefore, real-time access was important in this situation.

Apart from that, a cloud server was used to save the data that the device has collected previously. It was valuable for machine learning to analyze the users' data whenever it needed. The cloud server could be accessed by the host program, and it could download the data and process it while controlling the air conditioner. Also, the users could also take advantage on the cloud server function. The data collected from the user's device could show the user how the indoor environment was maintained by the smart air conditioner remote. It facilitated the user on understanding his indoor environment status.

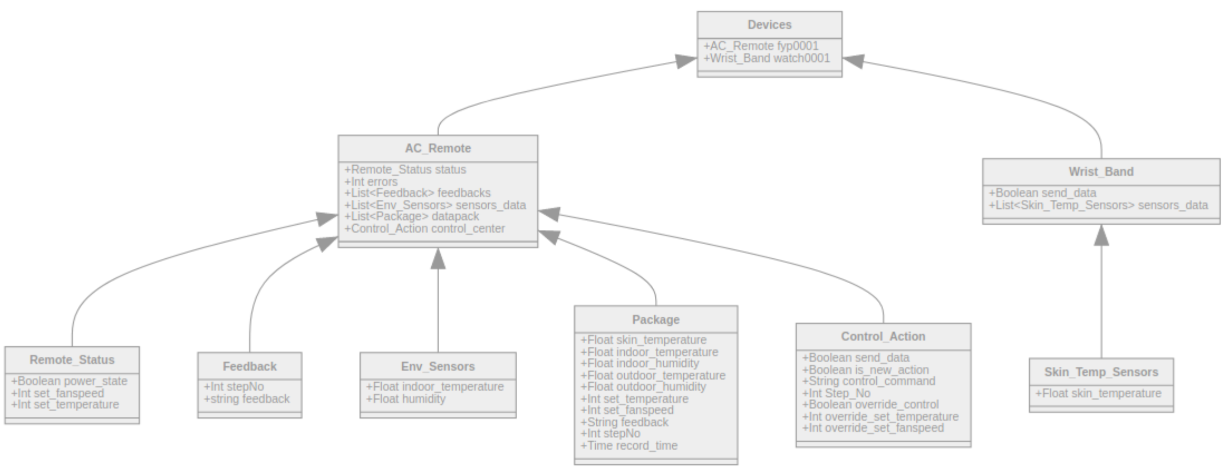

Figure 5-b Online database class diagram

5.2.1.3 Mobile Application

As the control feedback was needed to analyze the users' thermal comfort zone, the most convenience way for them to send the feedback is to use a mobile application to perform it. The mobile application should supply a multiple-choice button for the users to input their current thermal sensations. Also, it should provide information on their indoor environment status, so that they could understand whether the smart air conditioner device was working as they expected.

Apart from that, as the smart air conditioner remote was intended to replace the traditional air conditioner remote, it was also important that the smart air conditioner remote could manually control the air conditioner. Therefore, the mobile application should provide an override control action to the air conditioner whenever the user needed. This override control function should involve all the original control actions of the traditional air conditioner remote, so that the smart remote could be able to replace its position and provide more functionality to the users.

5.2.2 Hardware Development

The hardware development contains two sections, which are the smart air conditioner remote and the wrist skin temperature measuring device. These two devices mainly served as the sensors to collect the data of the environment and the user. Apart from that, the smart remote was also used to control the air conditioner, so that the control algorithm could update the environment data with its selection of action.

5.2.2.1 Smart Air Conditioner Remote

There are two main function for the air conditioner remote. The first one is to control the air conditioner according to the control tactics provided by deep neural network. The second one is to collect the indoor temperature and indoor humidity and send to the database. The data is collected remotely by running a hosting program on a computer. It will process the data and send the control actions to the device. To improve the feasibility of applying it to real world situation, the air conditioner remote should be connected to Wi-fi, so that the data could be transmitted instantly in any place. Figure 5-e

As it needed to replace the traditional air conditioner remote, it should be capable to send signals to the air conditioner. For normal traditional air conditioner remote, it used the infrared (IR) signals with 38kHz. [4] To analyze the IR signals, I used the program to plot different IR signals. Figure 5-c was the original IR signals, and by comparing the with the other IR signals, I was able to map the different between different and perform as mask function on the IR signals, which was shown in Figure 5-d. With the mask function, the smart air conditioner remote could be able to send command to the air conditioner by generating the same IR signals as the original air conditioner remote. The technique used in this process was the backward engineering method, by observing different output data and finding the relationship between the output data, so that the principle behind the device could be analyzed and rebuilt it.

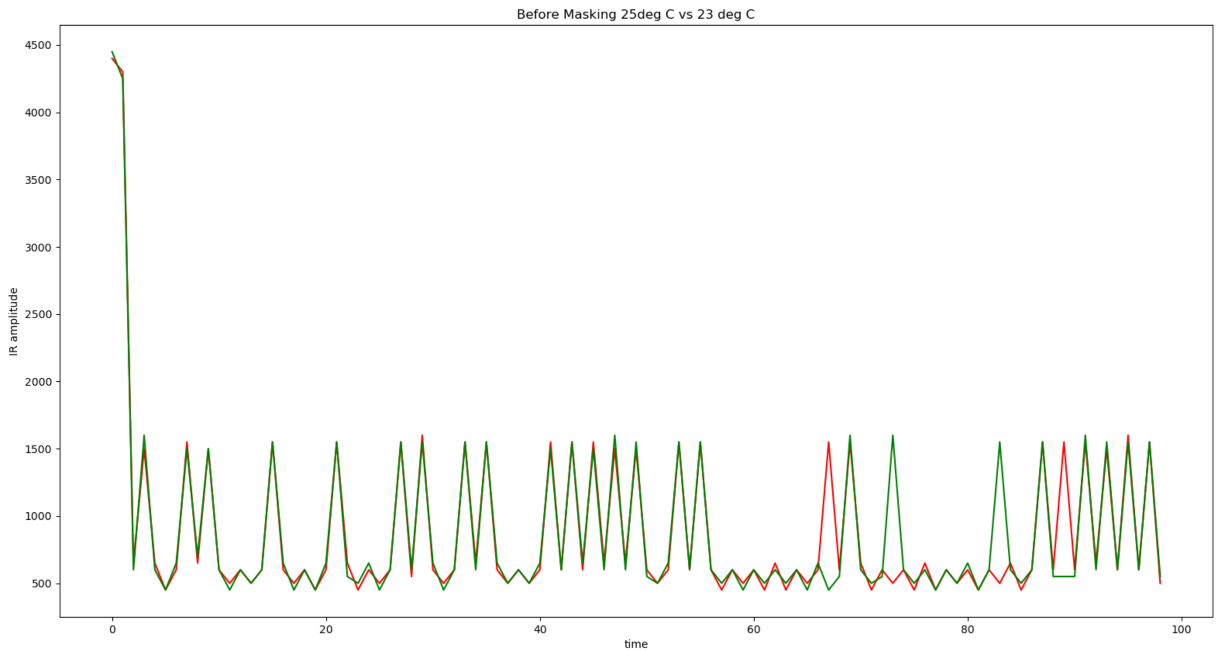

Figure 5-c before masking the infrared signals

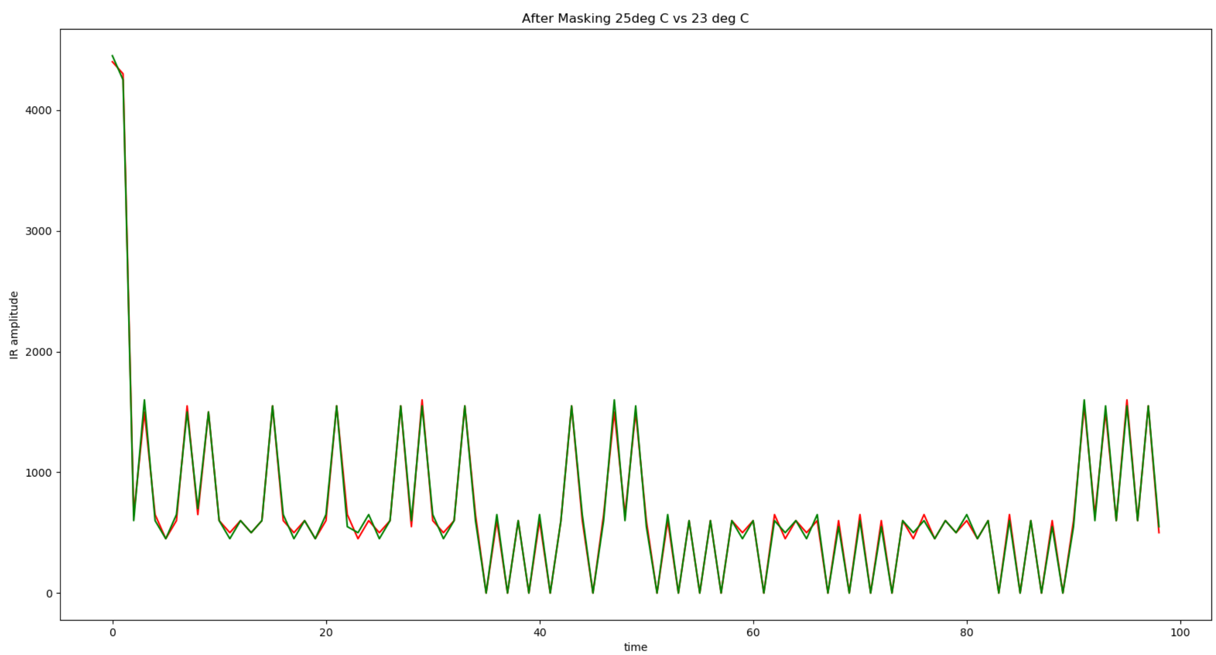

Figure 5-d after masking the infrared signals

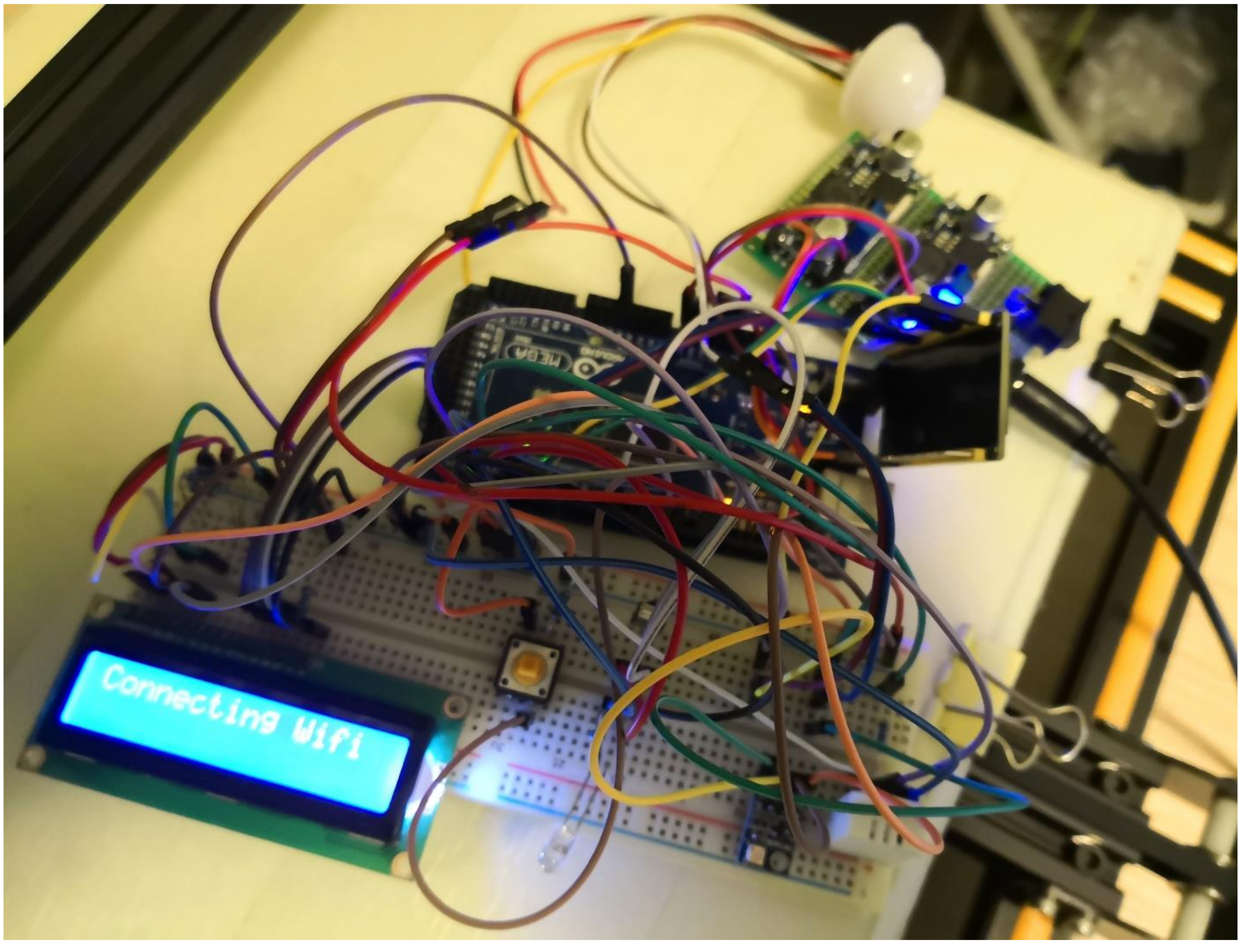

Figure 5-e smart air conditioner remote

5.2.2.2 Wrist Skin Temperature Measuring Device

There are different papers which studies the feasibility of estimating the thermal sensation by skin temperature, and one of the papers assessed the feasibility of wrist skin temperature monitoring for estimating subjective thermal. [5] The paper tests three wrist regions, which consist of the radial artery, ulnar artery and upper wrist. [5] The results for using one sensor to estimate the thermal sensation shows that the upper wrist region has a lower root mean square and higher accuracy than the other two regions. [5] Therefore, the upper wrist region is selected for the wrist skin temperature measure device.

To control the material cost, a low budget temperature sensor (DS18B20 digital thermometer) is applied to this device. From Figure 5-f, it showed that the DS18B20 sensor provided a metal case for waterproof function and better heat conduction, and its accuracy is about ± 0.5°C. The reason it needs to be waterproof is preventing the chance of short circuit due to user's sweating.

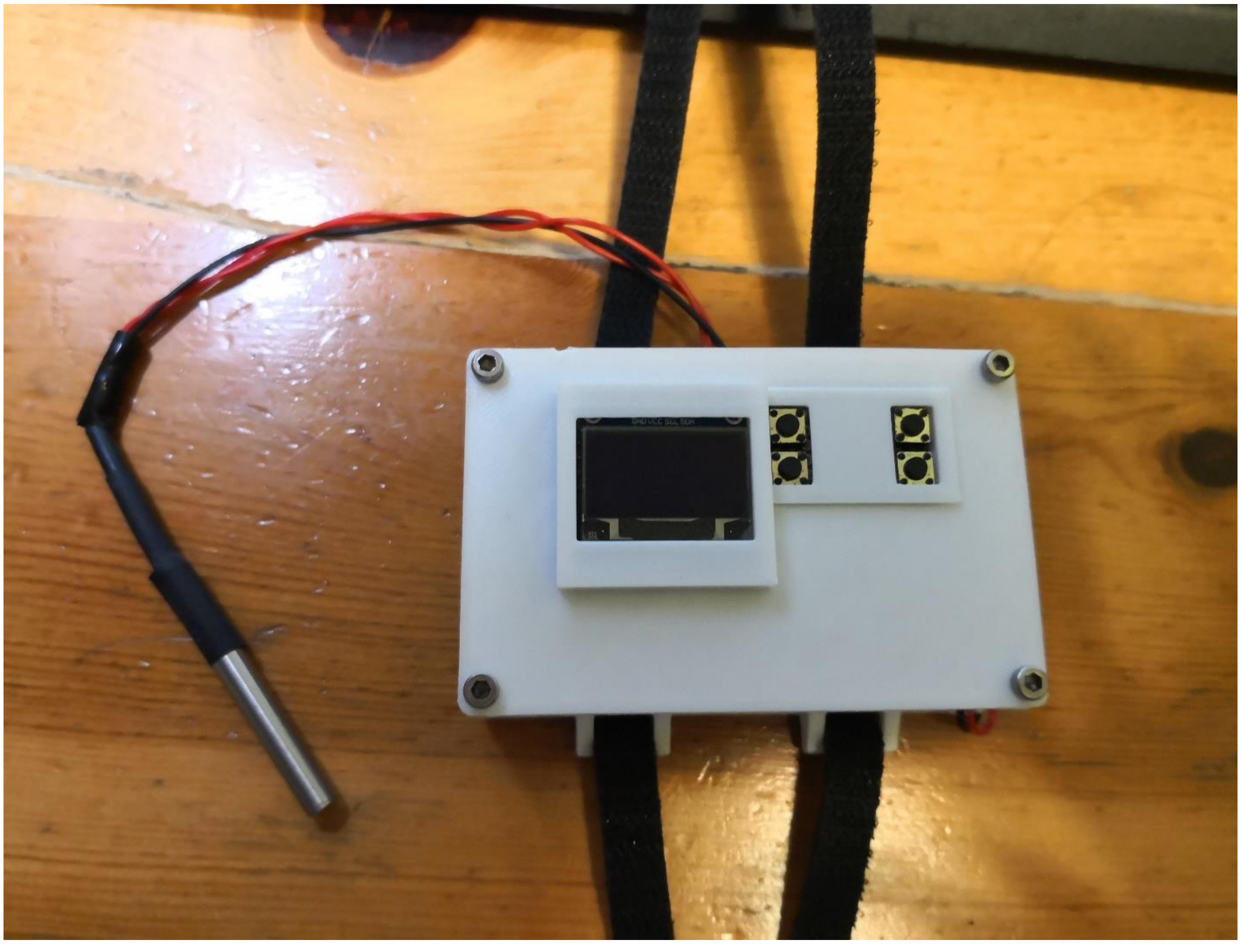

Figure 5-f wrist skin temperature device

6 Results and discussions

6.1 Deep Neural Network Analysis

The total data collected for analyzing the thermal comfort zone has 2981 data points. To perform cross validation, the data was split into 80% training data and 20% validation data. The result is shown below. The categorical cross-entropy loss for training and validation both reached the limit at about 100 epochs with batch size 24 and shared similar limits, which are between 0.94 and 0.98. The training and validation accuracy also shared similar results, which are about 60% shown in Figure 6-a. It indicated the DNN model may need more data points for further decrease the loss and increasing the accuracy. And it also implied that more feature may need to add into the model for higher accuracy prediction.

However, there was no significance separation between the training loss and the validation loss, which showed that the DNN was neither over fitting nor under fitting. And the training and validation accuracy were increasing steadily. They both implied the DNN had enough neurons and hidden layers for solving the thermal comfort classification problem. The DNN model has maximized the accuracy of classifying thermal comfort level by using only 4 environment data (both indoor and outdoor temperature and humidity), skin temperature and 2 control actions (set-temperature and set-fan-speed). One of the research papers studied on comparing whether using normalize skin temperature would improve the prediction of thermal comfort state. The paper indicated without using body surface area and clothing insulation to normalize the skin temperature will lower the accuracy of thermal comfort prediction which will have about 60% to 65% accuracy. [6] The result from that paper was comparable to the DNN result. It implied that the body surface area and clothing insulation could act as an input feature to the DNN for improving the overall accuracy.

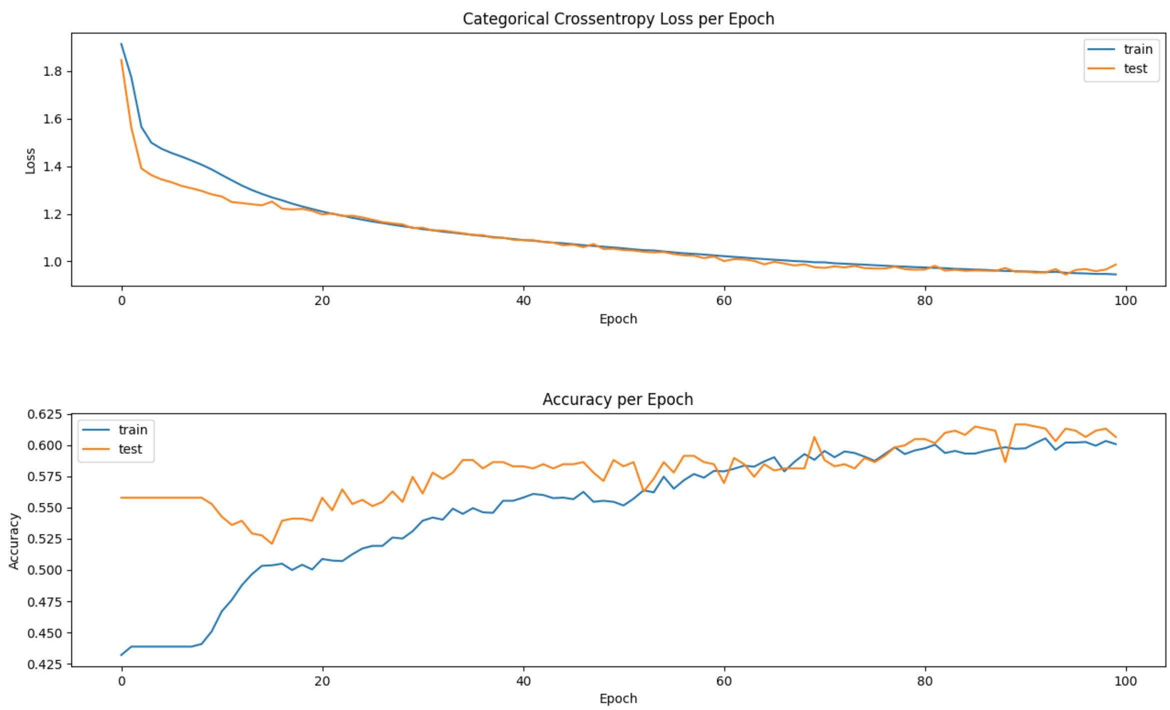

Figure 6-a loss and accuracy of the DNN

6.2 Environment Data Analysis

To analyze the relationship of the features, a correlation heat map was plotted to help understanding whether the two features will benefit the DNN on classifying thermal comfort. The two correlations, (indoor temperature, set-temperature) and (indoor humidity, set-temperature), shared similar values, which were 0.44 and 0.47. It indicated the set-temperature tends to affect the indoor environment with a linear relationship. However, the set-fan-speed did not show a strong correlation between the other features such as indoor temperature, indoor humidity and skin temperature, which indicated the set-fan-speed did not contribute much on the environment change.

For the correlations between the outdoor features and indoor features, they had stronger correlation indicated that the outdoor environment was constantly affecting the indoor environment. The correlations, (indoor temperature, outdoor temperature) and (indoor humidity, outdoor humidity), are 0.34 and 0.51. It implied that the set-temperature affected more to the indoor temperature than the outdoor temperature, while the outdoor humidity affected more to the indoor humidity than the set-temperature. The results reflected that the air conditioner deal with cooling better than dehumidification. The possible reason was the indoor environment was not to ideally conceal where the outdoor moisture could pass through from cracks and gaps, and it caused the indoor environment could not stay at the low level of humidity.

In Hong Kong, the relative humidity was mostly higher than 70% throughout the year, the indoor environment will mostly face the water vapor diffusion problem. And the air conditioner compressor needed to spend more energy on removing the moisture inside the room to kept operating at a certain temperature, which are lower than the dew point temperature. As the problem consists of the vapor resistance of the building materials, it could not be solved by changing the building materials. However, we could add materials with higher vapor resistance, such as foamed polyurethane or foamed polystyrene, to the wall to increase the vapor resistance. It was also useful to sealing the gaps between windows and walls and to close the fresh air duct when the humidity is high.

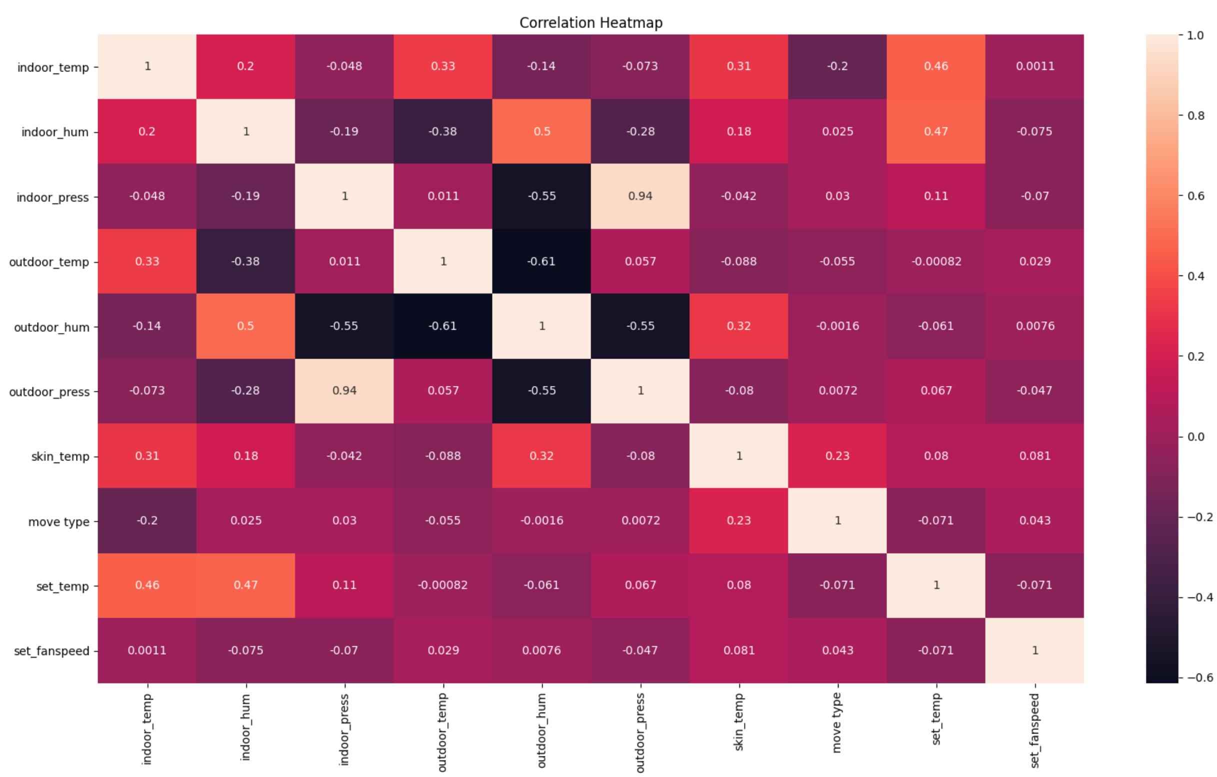

Figure 6-b correlation heatmap

6.3 Thermal Comfort Analysis

As we analyzed the environment data and discovered different relationship between the features, we should visualize the environment data with the thermal comfort levels. The graph showed how the thermal comfort level clustered in skin temperature data, indoor temperature data and indoor humidity data. In the distribution graphs, the means implied as the center the thermal comfort clusters. For the skin temperature, the center of the three hot clusters shifted from 33.56°C to 32.65°C, which was from “very hot” to “a bit hot”. The center of the three cold clusters shifted from 31.27°C to 32.22°C, which was from “very cold” to “a bit cold”. And the center of the comfy cluster was at 32.34°C. The “very cold”, “very hot” and “hot” clusters had smaller deviations, which implied that they were easier to classify than the other clusters. The “cold” and “a bit cold” clusters shared similar deviations and a small difference between the centers, so the classification between these two clusters were harder to be identified. A similar situation was also appeared in the “a bit hot” and “comfy” clusters. However, the “comfy” data showed a normal distribution from 30°C to 35°C that increases the precision on classifying the “comfy” clusters.

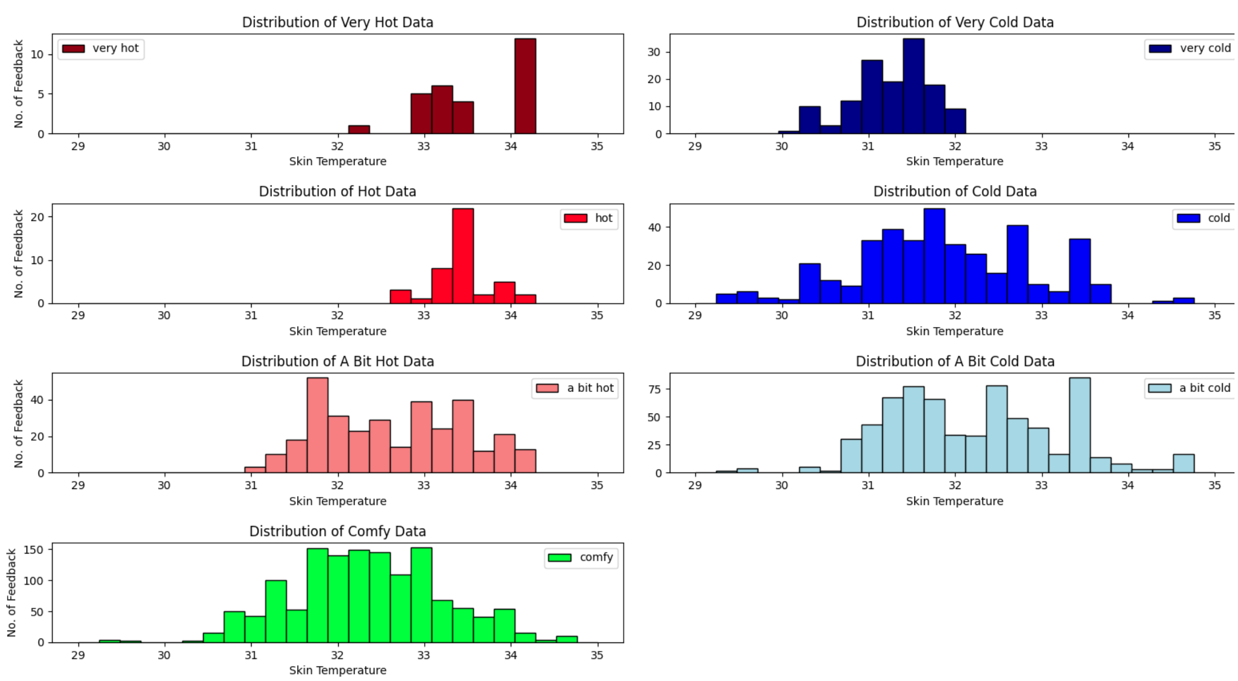

Figure 6-c skin termperature distribution graph

Skin Temperature		
Thermal Comfort Level	Mean	standard deviation
Very Cold	31.27	0.44
Cold	31.86	1.02
A Bit Cold	32.22	0.99
Comfy	32.34	0.88
A Bit Hot	32.65	0.81
Hot	33.42	0.30
Very Hot	33.56	0.55

For the indoor temperature, the centers of the three hot clusters shifted from 20.62°C to 22.18°C, while the centers of the three cold clusters shifted from 26.74°C to 24.40°C. And the center of the "comfy" cluster was at 23.43°C. The distribution graphs of the indoor temperature showed a much clear shifting properties with smaller deviation than the skin temperature. It indicated the tendency of the thermal comfort zone is established between small difference of skin temperature and larger difference of indoor temperature.

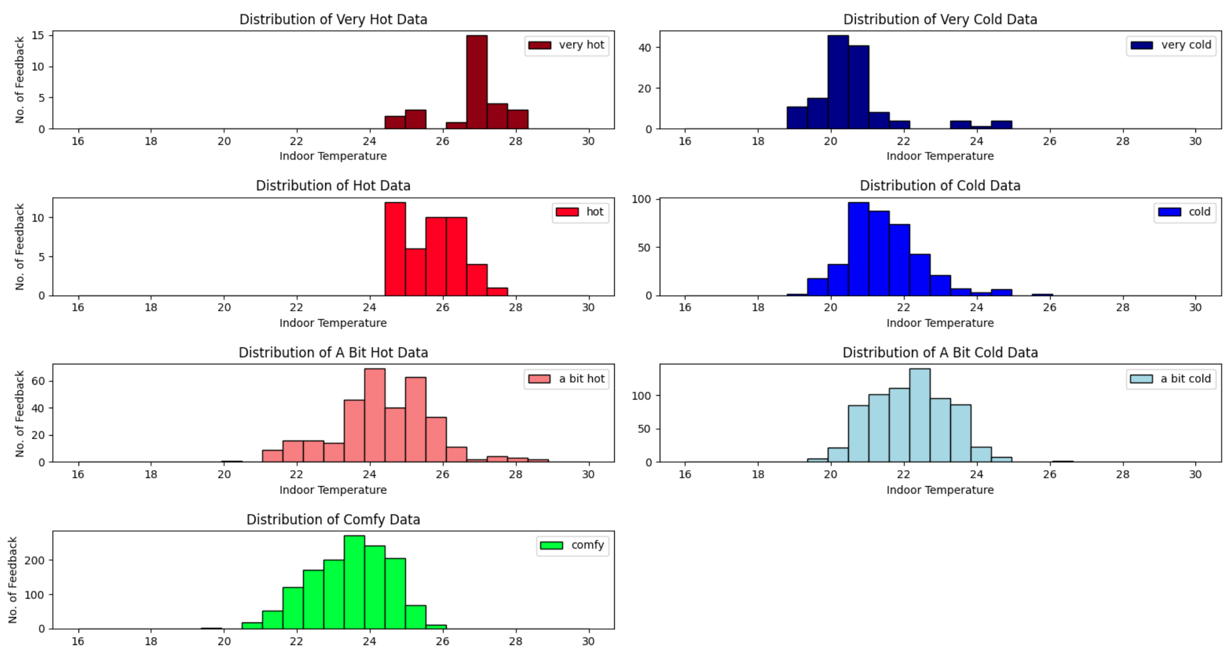

Figure 6-d indoor temperature distribution graph

Indoor Temperature		
Thermal Comfort Level	Mean	standard deviation
Very Cold	20.62	1.13
Cold	21.44	1.00
A Bit Cold	22.18	1.07
Comfy	23.43	1.10
A Bit Hot	24.40	1.36
Hot	25.72	0.73
Very Hot	26.74	0.93

Though the indoor humidity showed the same shifting properties, the deviation between different points were much larger compare to the other two data, especially for the three cold levels, they were more spread out to different humidity levels. It implied that the other features may affect the thermal comfort results. One of the situations was that with same level of humidity, the difference of set-temperature may affect the feedback from the user. For example, the humidity is at 50%, while the set-temperature could be set to 20°C or 24°C. The former setting will have larger probability to receive a cold feedback, while the latter will have larger probability to receive a comfy feedback.

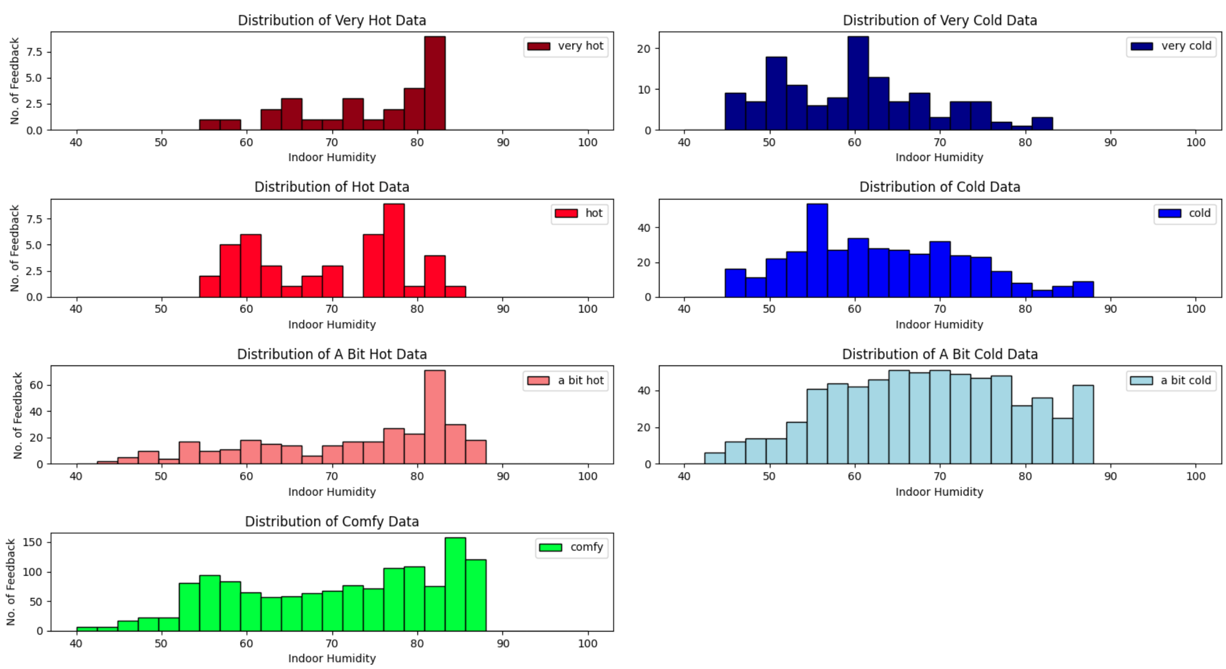

Figure 6-e indoor humidity distribution graph

Indoor Humidity		
Thermal Comfort Level	Mean	standard deviation
Very Cold	59.99	9.01
Cold	63.20	9.92
A Bit Cold	68.15	1.07
Comfy	70.35	12.13
A Bit Hot	72.17	11.75
Hot	69.65	8.84
Very Hot	74.07	8.22

By plotting the data in 2-dimensional plane, we could further visualize the clusters of the thermal comfort levels. There are two graphs, one was non-normalized, and one was normalized. For the skin temperature versus the indoor temperature, the “comfy” cluster tended to stay at the center of the plane. For the skin temperature versus the indoor humidity, all the clusters collided to each other, and the boundary of the classifier of the “comfy” cluster was hard to determine. It implied that only with skin temperature and indoor humidity may not enough to classify the thermal comfort, and it may even lower the accuracy. However, for the indoor temperature versus indoor humidity graph, the “comfy” cluster had a clearer decision boundary, and so as the other clusters.

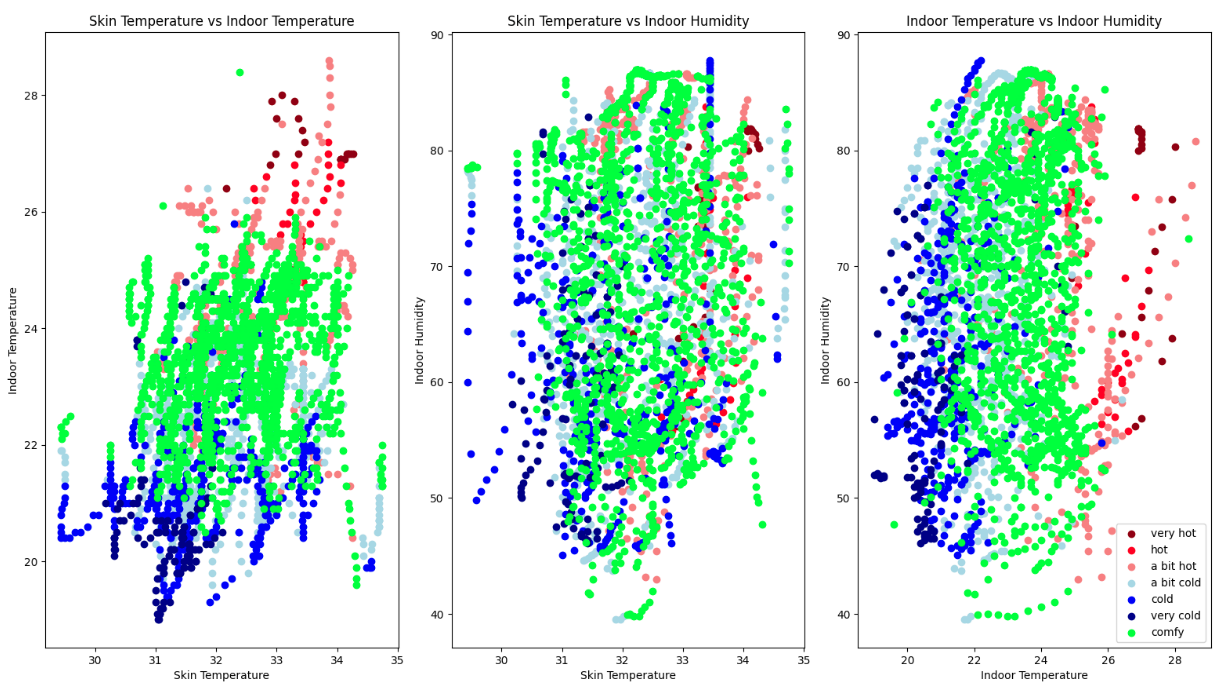

Figure 6-f non-normalized 2d plots

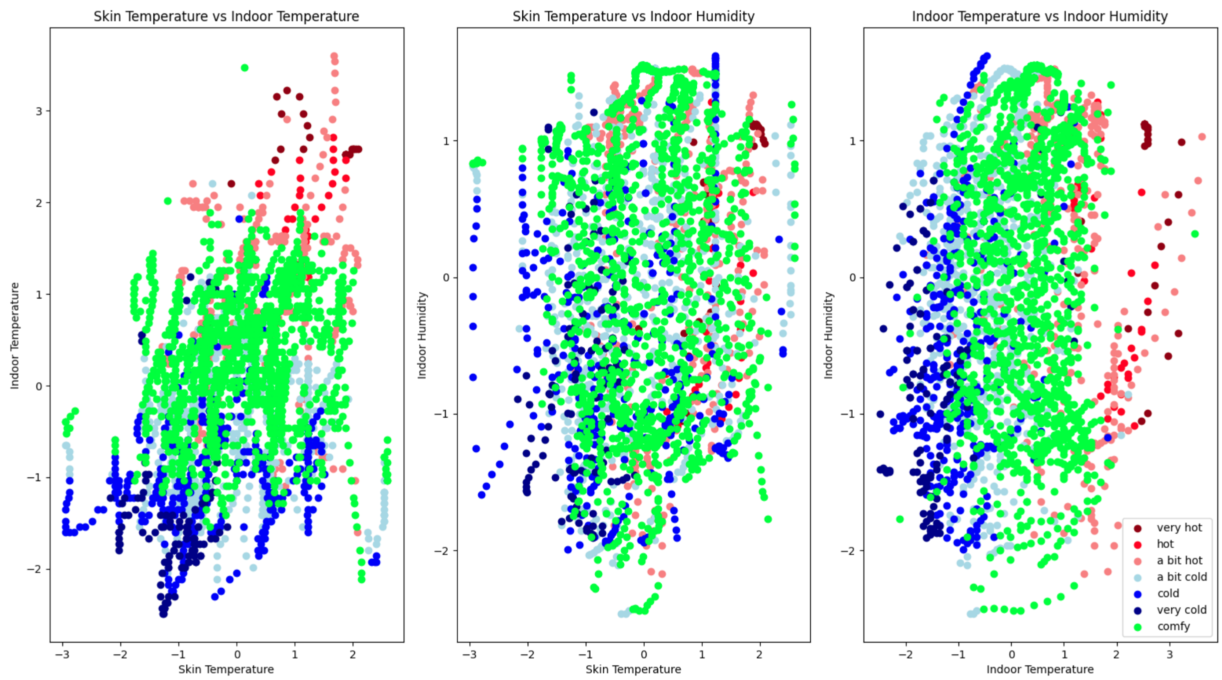

Figure 6-g normalized 2d plots

The 3-dimensional graph showed the thermal comfort zones generated by the indoor temperature, the indoor humidity and the skin temperature. Three main color for dividing the thermal comfort zones, where color blue represented the cold data, color red represented the hot data, and color green represented the comfy data, while the other colors were the different levels on cold and hot data. From the graph, different thermal comfort levels appeared to have their own clusters and centers. For example, the cold region was focused on about 22°C, while the hot data was focused on about 26°C. And the comfy data was clustered between the hot and cold region. It implied that the thermal comfort zone was possible to be clustered into different regions using a 3-dimensional model. And by increasing the dimensionality of the classifier, the thermal comfort zone was possible to have a clearer decision boundary.

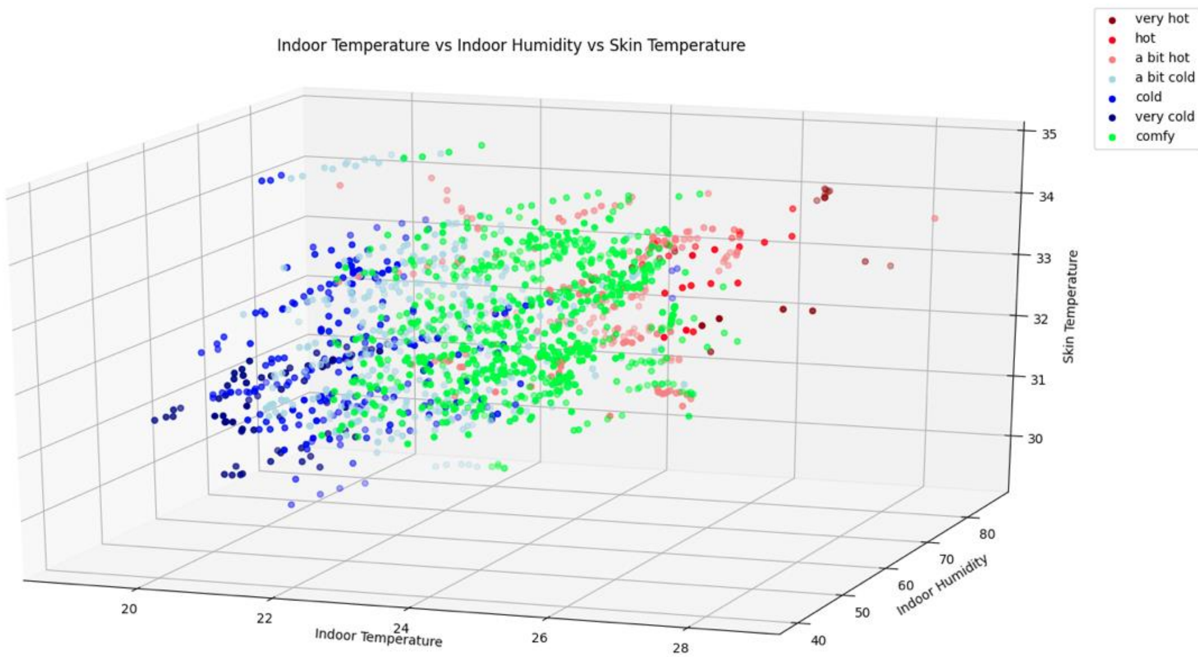

Figure 6-h 3D plots

6.4 Control Algorithm

By using the DNN model, it could predict the user's feedback at different states. For the input features the control algorithm will input to the DNN, it collected the current environment data, which are indoor temperature, indoor humidity, outdoor temperature, outdoor humidity and skin temperature. Then, it created a list containing all the combination of the control actions. For this project, the air conditioner had total 27 control actions, which consists of 9 temperatures setpoints and 3 fan-speed setpoints. The range of the temperature setpoint was from 17°C to 25°C. And the fan-speed had 3 levels of the wind power setting. After creating the combination list, every control action combined with the environment data, which will create list of features with 27 rows.
Then, by inputting the list to the DNN, it returned a probability distribution list of the thermal comfort level. The probability distribution list showed which control actions will have larger chance to receive the user's comfort feedback. Thus, we can sort the list and find out the best control action of the current state.
However, if every step it took was the best control action at the current state, it is a greedy algorithm that tried to maximize the user comfort at every state. It may be good to the user that could have best thermal comfort at every state, but it will not be able to foresee the possible outcome of its action, which may lead to problem like overcooling.

To prevent the control action be greedy algorithm, it needed to estimate the future possible outcomes, which was the future user's comfort level. The solution was to take a second thermal comfort prediction with the future states, which are the future environment data and the first prediction control actions. To retrieve the future environment data, we assume the outdoor temperature and outdoor humidity did not change significantly. For the skin temperature, we limited the future skin temperature to be lower than or equal to the current skin temperature, if the current control action intended to cool down where the next set-temperature was lower than the current set-temperature, vice versa.

After that, it accessed all the history data points and found out the lowest indoor temperature and indoor humidity with the corresponding future environment data. As the exact datapoints of outdoor temperature and outdoor humidity may not be exist, and the future skin temperature prediction was an inequality, the returns may have multiple lowest indoor temperature and indoor humidity. The multiple returns were the possible future scenarios that the algorithm would meet if it took that control action. Then, by inputting all the possible future scenarios to the DNN, it output the probability distribution of the future user's feedback. It could find out the average probability of getting a user comfort feedback. It then repeated the second prediction steps for the sorted control actions.

After that, it would have two lists. One was the average probability list of getting a user comfort feedback in the future state. And one was the probability list of getting a user comfort feedback in the current state. By comparing two probability lists, it could select the action that was more balanced on both current and future feedback. This method was applicable on both cooling and heating process. The heating process refers to the situation where the set-temperature was higher than the indoor temperature.

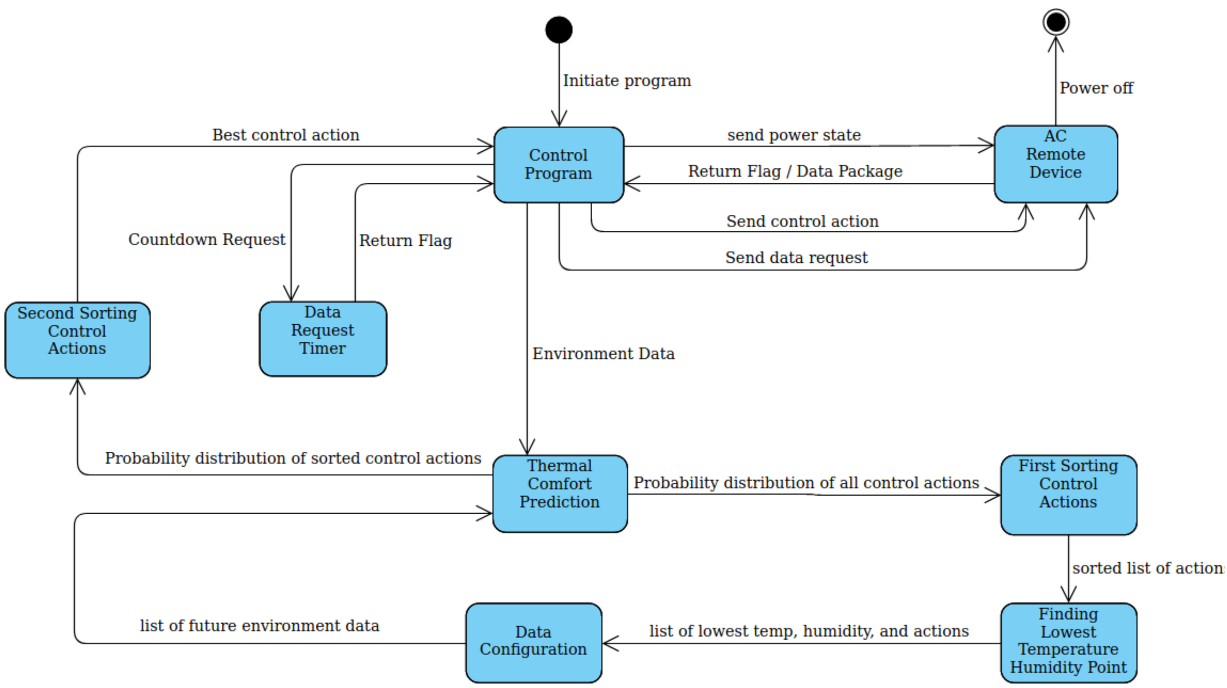

Figure 6-i state diagram of the control algorithm

7 Conclusion

The skin temperature and indoor temperature relation results displayed a perspective of the combining the user data with the environment data. By analyzing the data, it showed the potential of the defining the thermal comfort zone with higher dimensions. Though indoor humidity did not perform good result on its own, the hidden relation between the indoor humidity and other features may not be found yet. A more complex analysis may need to discover more potential features that could affect the thermal comfort zone.

The result of the thermal comfort prediction showed that the input features for the deep neural network may not be enough, so that the hypothesis function could not analyze enough, and the accuracy of the prediction maintain at 60%. However, the model was only trained using about 2400 datapoints, which have only about 20 hours of data. It could be more generalized if more data were fed into the neural network.

Though the accuracy was about 60%, it could act as a base model of the thermal comfort prediction. It means that the other training data will be accumulated and fed into the neural network every time after the control algorithm ends. This process could enhance the neural network to find out the wrong thermal comfort prediction. As the control algorithm assumes the prediction is not biased, it will perform calculation on the probability receive from the neural network. Therefore, with more training the neural network could auto correct the wrong prediction, and the model will shape to the specific user.

8 References

[1] S. J. L. Lynette A. Jones, Human Hand Function, New York: Oxford University Press, 2006.

[2] E. Alpaydin, Introduction to Machine Learning, London: The MIT Press, 2010.

[3] Zhilu Zhang,Mert Sabuncu, "Generalized Cross Entropy Loss for Training Deep Neural Networks with Noisy Labels," *NIPS,* vol. 31, no. Advances in Neural Information Processing Systems, 2018.

[4] "IR Communication," SparkFun Electronics, 7 2 2013. [Online]. Available: https://learn.sparkfun.com/tutorials/ir-communication/all. [Accessed 29 12 2019].

[5] Soo Young Sim, Myung Jun Koh, Kwang Min Joo, Seungwoo Noh, Sangyun Park, Youn Ho Kim, Kwang Suk Park, "Estimation of Thermal Sensation Based on Wrist Skin Temperatures," *MDPI,* vol. 16, no. Sensors 2016, p. 420, 2016.

[6] Tanaya Chaudhuri,Deqing Zhai,Yeng Chai Soh,Hua Li,Lihua Xie, "Thermal comfort prediction using normalized skin temperature in a," *Elsevier,* vol. 159, no. Energy and Buildings, pp. 426-440, 2017.

9 Appendix

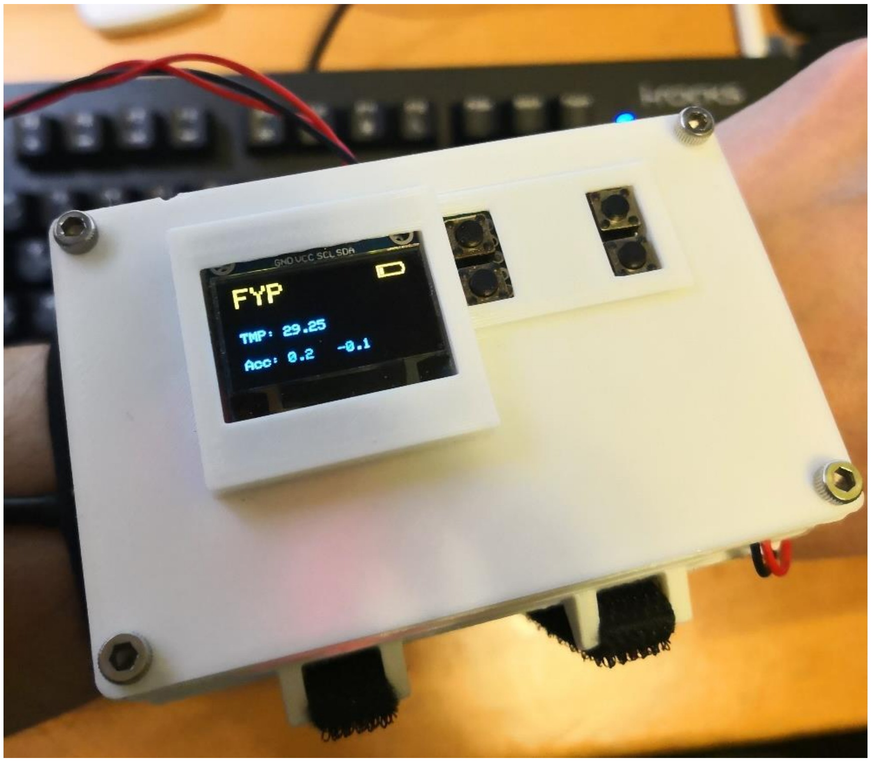

Figure 9-a test run on the wrist skin temperature measuring device

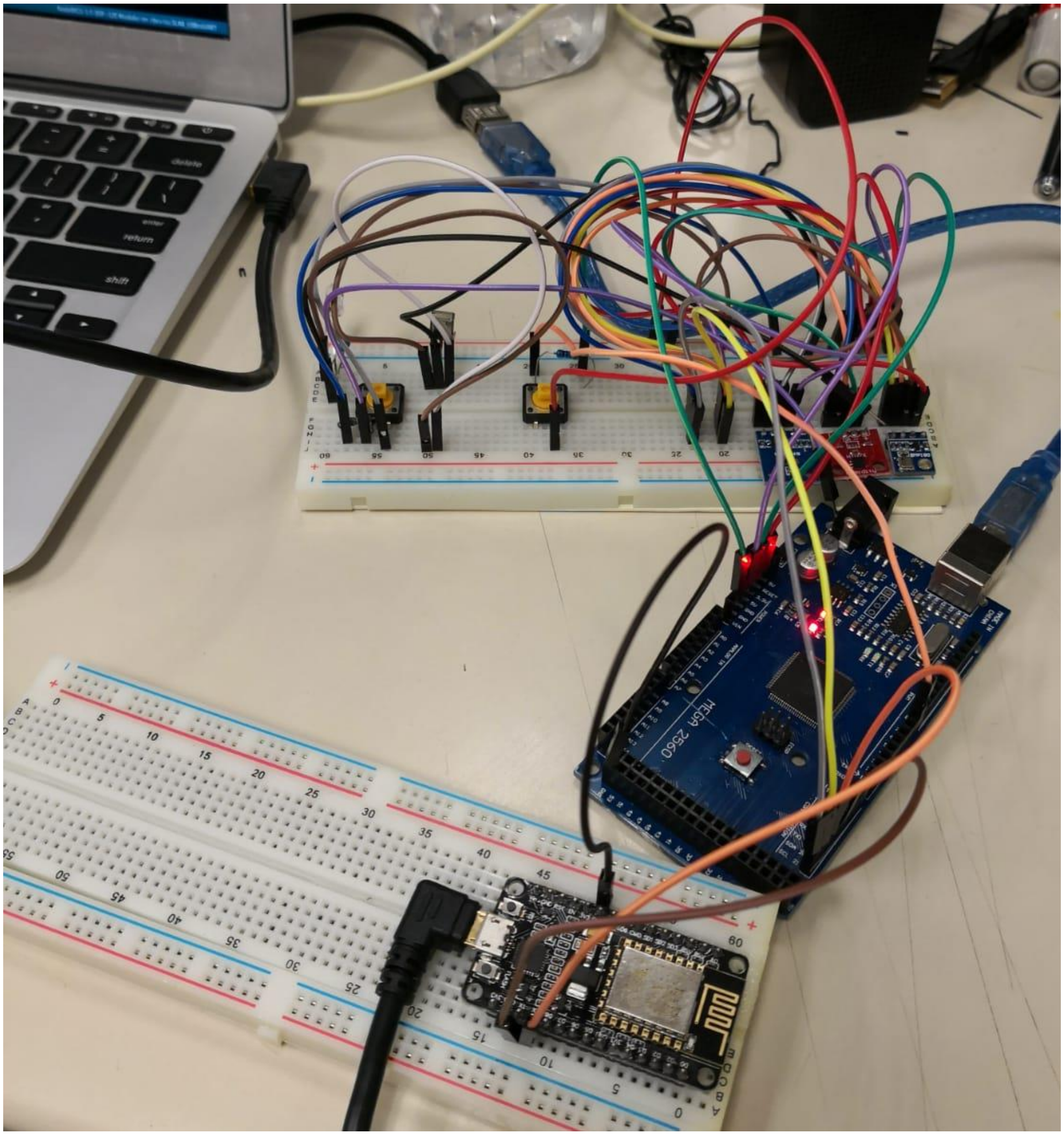

Figure 9-b test run on connecting to the online database